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A Conceptual Evaluation of Sustainable Variable-Rate Agricultural Residue Removal

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Agricultural residues have near-term potential as a feedstock for bioenergy production, but their removal must be managed carefully to maintain soil health and productivity. Recent studies have shown that subfield scale variability in soil properties (e.g., slope, texture, and organic matter content) that affect grain yield significantly affect the amount of residue that can be sustainably removed from different areas within a single field. This modeling study examines the concept of variable-rate residue removal equipment that would be capable of on-the-fly residue removal rate adjustments ranging from 0 to 80%. Thirteen residue removal rates (0% and 25–80% in 5% increments) were simulated using a subfield scale integrated modeling framework that evaluates residue removal sustainability considering wind erosion, water erosion, and soil carbon constraints. Three Iowa fields with diverse soil, slope, and grain yield characteristics were examined and showed sustainable, variable-rate agricultural residue removal that averaged 2.35, 7.69, and 5.62 Mg ha^{-1}, respectively. In contrast, the projected sustainable removal rates using rake and bale removal for the entire field averaged 0.0, 6.40, and 5.06 Mg ha^{-1}, respectively. The modeling procedure also projected that variable-rate residue harvest would result in 100% of the land area in all three fields being managed in a sustainable manner, whereas Field 1 could not be sustainably managed using rake and bale removal, and only 83 and 62% of the land area in Fields 2 and 3 would be managed sustainably using a rake and bale operation for the entire field. In addition, it was found that residue removal adjustments of 40 to 65% are sufficient to collect 90% of the sustainably available agricultural residue.

Over the past three decades, significant discussion and debate have taken place regarding the opportunity for sustainable removal of agricultural residues for bioenergy production. The latest motivation for investigating agricultural residue removal potential comes from the Energy Independence and Security Act (2007), which requires annual U.S. biofuel production to increase to more than 136 billion liters by 2022. Noncornstarch feedstock, such as agricultural residues, must comprise nearly 80 billion liters of this production. If a production rate of 330 liters of biofuel per metric ton of biomass feedstock is assumed (Aden et al., 2002; Phillips et al., 2011), meeting this target will require the development and utilization of over 240 million metric tons of noncornstarch biomass resources annually. Many in the bioenergy community consider sustainable agricultural residues to be the cellulosic resource with the greatest near-term potential for bioenergy production (Perlack et al., 2005; Aden et al., 2002). Agricultural residues provide a number of functions within the agronomic system that are critical to maintaining soil health (Karlen et al., 2003; Johnson et al., 2006; Wilhelm et al., 2007; Clay et al., 2010), and excessive residue removal can negatively affect the long-term productivity of soil resources (Wilhelm et al., 2010; Sheehan et al., 2004; Mann et al., 2002; Khan et al., 2007).

A number of previous efforts have investigated the issue of sustainable residue removal across a wide range of spatial scales and analysis approaches. These have identified that significant amounts of agricultural residues are potentially available for bioenergy production. An early study performed by Larson (1979) examined agricultural residue removal potential across the Corn Belt, Great Plains, and the Southeast of the United States. Because of data and computational limitations, this study used area-weighted averages for soil characteristics, climate conditions, and crop yields across the USDA-identified major land resource areas (MLRAs) (USDA–NRCS, 2012a) for the regions investigated. The scale of MLRAs is typically groups of 5 to 20 counties. To do this, Larson aggregated the soils data available to create a composite set of erodibility factors representing each

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Abbreviations: LiDAR, light detection and ranging; MLRA, major land resource area; RUSLE2, Revised Universal Soil Loss Eq. [2]; SCI, Soil Conditioning Index; SSURGO, Soil Survey Geographic Database provided by the Natural Resources Conservation Service; WEPS, Wind Erosion Prediction System.
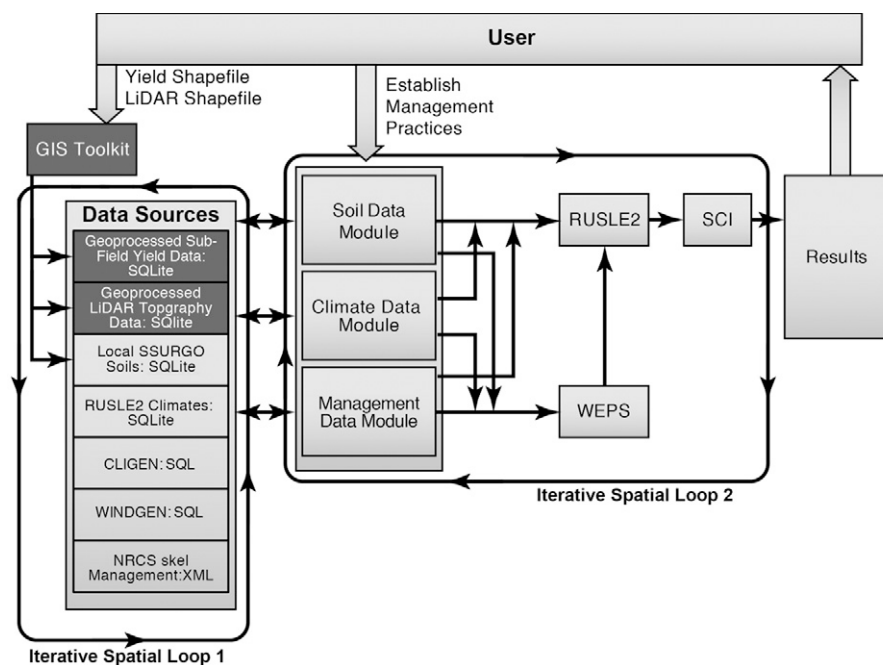
Fig. 1. The subfield scale modeling process including the databases, models, and data flow through the integrated model. LiDAR, light detection and ranging; NRCS, Natural Resources Conservation Service; RUSLE2, Revised Universal Soil Loss Eq. [2]; SCI, Soil Conditioning Index; SSURGO, Soil Survey Geographic Database provided by the Natural Resources Conservation Service; WEPS, Wind Erosion Prediction System.

MLRA and estimated that nearly 49 million metric tons of agricultural residue could be sustainably harvested over the regions assessed at that time. After an extended period in the 1980s and 1990s during which agricultural residue removal received limited research focus, Nelson (2002) used the Soil Survey Geographic (SSURGO) Database (USDA–NRCS, 2011c), an open access national soil survey database provided by the USDA Natural Resources Conservation Service (NRCS) to investigate residue removal potential for 37 states from the Great Plains to the East Coast. Nelson developed a methodology using "county average, hectare-weighted fields." This methodology aggregated the range of soil characteristics for each county and concluded at that time the 37 states investigated could annually produce approximately 58 million metric tons of residue in a sustainable manner. Continued progress with data management and environmental modeling tools enabled Nelson et al. (2004) to adapt the 2002 Nelson study to (i) include additional crop rotations and (ii) calculate erosion at the SSURGO soil type spatial scale (10–100 m). Based on this, Nelson et al. (2004) concluded that 30.2 million dry metric tons of corn (*Zea mays* L.) stover and 13.4 million dry metric tons of wheat (*Triticum aestivum* L.) straw were available for removal annually across the 10 states investigated over the 5-yr span from 1997 to 2001. In 2007, Graham et al. used the methodology developed by Nelson et al. (2004) to investigate corn stover residue removal across the United States. The study by Graham et al. (2007) used the same spatial scale, or scenario tools, as the 2004 study by Nelson et al. and included an additional constraint of soil moisture. Graham et al. (2007) also found that soil organic carbon was an important consideration but noted significant computational limitations to including it. They stated "in its current form with manual input, the Soil Conditioning Index is not practical to run for the thousands of corn production situations that occur in the USA." The study concluded that 58.3 million metric tons of stover could be sustainably removed annually.

Cruse and Herndl (2009) noted that developing a sustainable and profitable cellulosic biofuels industry using corn stover will require the ability to determine spatially variable sustainable removal rates and harvest technology that can remove residue at these rates. Significant work has been done looking at single-pass and multi-pass residue removal system configurations and quantifying the generalized removal potential of the different systems. These systems have generally not been capable of variable-rate removal. Single-pass configurations have much more potential for on-the-fly adjustments of removal rate than multipass configurations, and some investigations of variable-rate, single-pass configurations have been performed. Karkee et al. (2010) presented a study in which subfield removal adjustments were made using the single-pass equipment configuration used by Hoskinson et al. (2007). Similar to variable-rate seeding (Fountas et al., 2006; Bullock et al., 1998), variable-rate fertilizer application (Hong et al., 2006; Koch et al., 2004), and variable-rate chemical application (Anglund and Ayers, 2003), the availability of high-spatial-resolution agriculture datasets provides significant motivation for developing variable residue removal equipment. Based on single-pass technologies that include removal rates from 25% (Zych, 2008) to more than 80% (Hoskinson et al., 2007), the study presented here assumes an adjustable on-the-fly removal rate of 25 to 80% in 5% increments, with a 0% removal option.

Muth et al. (2012) developed an integrated modeling approach that uses high-spatial-resolution agricultural datasets to examine the variability of subfield agricultural residue removal (Fig. 1). This integrated model coupled the Revised Universal Soil Loss Equation, Version 2 (RUSLE2) (USDA–NRCS, 2011a), Wind Erosion Prediction System (WEPS) (USDA–ARS and NRCS, 2008), and Soil Conditioning Index (SCI) (USDA–NRCS, 2012b) models with a multiscale set of databases describing crop yield, surface topography, soil characteristics, climate, and land management data. The sustainability of rake and bale

residue removal of three fields in Iowa was examined using the current NRCS conservation management planning guidelines (USDA–NRCS, 2011b) and the subfield modeling approach. Rake and bale residue removal was modeled using NRCS operational assumptions that include raking on the same day as grain harvest, with baling occurring 2 d later. The removal rate for the modeled system is approximately 50% but varies slightly with crop rotation. The NRCS conservation management planning analysis concluded that rake and bale removal would be sustainable for two of the three fields. The subfield model demonstrated that there was significant variability in the sustainability of rake and bale removal across individual fields. As a consequence, the study concluded that the dominant critical soil and slope and the field average yield assumptions used in the NRCS conservation management planning may lead to unsustainable residue removal decisions for portions of some fields and reduced residue removal in other fields.

One potential approach for dealing with subfield scale variability in sustainable residue removal rates is to use equipment that can perform controlled, on-the-fly removal rate adjustments. Although it is becoming more broadly recognized that removal rates vary from field to field and within fields (Cruse and Herndl, 2009), limited work has focused on identifying the impact and value of equipment with this capability. This paper investigates sustainable variable-rate residue removal at the subfield scale for three representative Iowa fields. Specifically, the impact of a conceptual single-pass residue harvester configuration that can make on-the-fly removal rate adjustments is investigated using the subfield scale model developed by Muth et al. (2012). The previous study developed the integrated model and established that subfield variability in soil characteristics, surface slope, and grain yield can lead to significant variability in sustainable residue removal rates across a field. This study extends the earlier model to explore the impact of variable-rate residue removal on sustainably available residue. The results of variable-rate harvest using this conceptual machine are compared with sustainable rake and bale removal of agricultural residue using NRCS planning guidelines. In addition, this study quantifies the potential impact of various equipment residue removal capabilities.

Materials and Methods

In this study, the integrated model developed by Muth et al. (2012) to support sustainable subfield scale residue removal assessments is used to examine sustainable, variable-rate agricultural residue removal potential using a conceptual variable-rate harvesting system. Figure 1 shows the dataflow within the subfield integrated model. A computational scheduling algorithm manages two iterative loops. The first loop implements a geoprocessing tool (ESRI ArcGIS 10) to organize the data from different spatial scales to be consistent with the crop yield data points that represent the base spatial unit for this analysis. The second iterative loop organizes the data inputs into the formats required for the integrated models. Approximately 1200 model executions per hectare (400 spatial elements, one management scenario, and three model executions [RUSLE2, WEPS, SCI] per spatial element) are required. Results are provided to the user through an SQLite database.

Assembly of data and execution of the models requires resolving information at different spatial scales between the various databases. It is important to recognize the implications of using each of the integrated models within this multiscale framework. RUSLE2 has been developed with the base computation unit as a single overland flow path along a hillslope profile and for conservation planning where a particular overland flow path is selected to represent a field. Conservation planning guidelines select a management practice that controls erosion adequately for that flow path profile. The conservation management planning application of RUSLE2 requires selection of a representative soil, slope, slope length, and yield that are considered constant for the field. To use RUSLE2 at the subfield scale, the assumption is made that the soil, slope, and yield characteristics at each base spatial element provide the representative overland flow path for the field. This is a reasonable approach but must be applied with care. Each base spatial element does not exist as an independent entity but rather is influenced by its neighboring elements. This is an important assumption that needs additional review and consideration, but, as discussed in Muth et al. (2012), significant insight can be gained by applying RUSLE2, WEPS, and SCI at the base spatial element scale. A similar assumption is made for WEPS, which models a three-dimensional simulation region representing a field or a small set of adjacent fields. The assumption made to use WEPS in the subfield scale integrated model is that the soil, slope, and yield characteristics for a spatial element in question are representative of a field-scale simulation region. The SCI is modeled for each spatial element by using the SCI subfactors calculated by RUSLE2 and WEPS using the assumptions as stated. The specific spatial details for each database used in the integrated model are provided in Muth et al. (2012).

In this study, agricultural residue removal rates based on commercially available equipment configurations are contrasted with removal rates based on a conceptual variable-rate residue removal equipment configuration in the same three Iowa fields and using the same management practices evaluated by Muth et al. (2012). These fields are described in Tables 1 and 2. These three fields were chosen for this series of studies because of the availability of high-spatial-resolution subfield scale data and because they exhibit a wide range of subfield scale variability of soil conditions, surface topography, and yield. Two of the fields are in a continuous corn crop rotation, and the other is in a corn–soybean [*Glycine max* (L.) Merr.] rotation. The list of operations used to describe these two rotations is shown in Table 3. These operation lists are consistent with the NRCS standards in the region where all three of the fields are located. These standards specifically include the timing of field operations and the type of equipment that is used for field operations. Two of the fields are modeled with reduced tillage practices, and one is modeled with conventional tillage practices, each representative of the tillage practices implemented in these fields (Table 3). The SSURGO soils that make up each field are shown in Table 1. The model assumptions and configurations for each tillage regime are consistent with the tillage definitions provided by the Conservation Technology Information Center (CTIC, 2012). Conventional tillage includes full-width tillage passes and results in less than 15% of the residue remaining on the soil surface after planting the next crop. Reduced tillage again involves full-width tillage passes but leaves up to 30% of the residue on the soil surface after planting.

Table 1. Soil Survey Geographic Database soils for each field and identification of the field characteristics required for conservation management planning assessment using Natural Resources Conservation Service guidelines. These characteristics include the dominant critical soil and slope representing each field, the field average grain yield, and the residue removal operations.

Field	Complete list of SSURGO† soils comprising each field (in order of area: high to low)	Dominant critical soil for each field from NRCS‡ guidelines	Dominant critical slope for each field from NRCS guidelines	Field average corn grain yield	Residue harvest operations
				Mg ha^{-1}	
1	84 Clyde silty clay loam, 0–2% slopes	83B Kenyon loam	4.0%	10.85	rake and bale
	198B Floyd loam, 1–4% slopes				
	173 Hoopeston fine sandy loam, 1–3% slopes				
	83B Kenyon loam, 2–5% slopes				
	407B Schley loam, 1–4% slopes				
	175B Dickinson fine sandy loam, 2–5% slopes				
	41B Sparta loamy fine sand, 2–5% slopes				
2	688 Koszta silt loam, 0–2% slopes	688 Koszta silt loam	1.0%	12.60	rake and bale
	587 Chequest silty clay loam, 0–2% slopes				
3	587 Chequest silty clay loam, 0–2% slopes	587 Chequest silty clay loam	1.0%	12.40	rake and bale
	687 Watkins silt loam, 0–2% slopes				
	88 Nevin silty clay loam, 0–2% slopes				
	7 Wiota silty clay loam, 0–2% slopes				
	133 Colo silty clay loam, 0–2% slopes				
	688 Koszta silt loam, 0–2% slopes				
	8B Judson silty clay loam, 2–5% slopes				
	422 Amana silt loam, 0–2% slopes				
	54 Zook silty clay loam, 0–2% slopes				

† Soil Survey Geographic Database.

‡ Natural Resources Conservation Service.

Table 2. Descriptions and characteristics of the three fields investigated in this study, including field size, crop rotation currently being used, and the tillage practices consistent with Conservation Technology Information Center definitions.†

Field	Location	Area	Crop rotation	Tillage
		ha		
1	Cerro Gordo County, Iowa	57	corn–soybean	reduced
2	Iowa County, Iowa	19	continuous corn	reduced
3	Iowa County, Iowa	77	continuous corn	conventional

† Definitions from CTIC (2012).

Table 3. Identification of the specific field operations and timing of field operations for the continuous corn and corn–soybean crop rotations modeled in this study with reduced tillage assumptions.†

Continuous corn		Corn–soybean	
1 Nov., year 1	chisel plow	20 Apr., year 1	fertilizer application
25 Apr., year 2	fertilizer application	1 May, year 1	field cultivation
1 May, year 2	field cultivation	1 May, year 1	plant corn
1 May, year 2	plant corn	11 Oct., year 1	harvest corn grain direct bale residue
11 Oct., year 2	harvest corn grain DB residue	1 Nov., year 1	chisel plow
		15 May, year 2	plant soybeans
		1 Oct., year 2	harvest soybeans

† Assembled from the Natural Resources Conservation Service operations database.

The subfield model uses high-spatial-resolution input data sets providing soil characteristics, surface slope, and grain yield. Crop yield data are supplied from the combine harvester yield monitor systems and represent actual yield data from the 2010 harvest provided by the farmers who supported this study. Each crop yield data point is a base spatial unit for the subfield scale integrated model, and each of these points represents a spatial element at the 1-m scale. Surface topography data are supplied by light detection and ranging (LiDAR) through airborne laser scanning (Vitharana et al., 2008; McKinion et al., 2010). The LiDAR data for the state of Iowa are provided by the Geo-TREE LiDAR mapping project and are managed in an SQLite database within the integrated model (GeoTREE, 2011). The LiDAR data are also provided at the 1-m scale. Soil characteristics data are provided by the Soil Survey Geographic (SSURGO) Database (USDA–NRCS, 2011c), an open-access national soil survey database provided by NRCS. The SSURGO data are at the 10- to 100-m scale. Climate data are represented in the integrated model at the county scale ($\sim$10,000–100,000 m) and are provided by three sources: NRCS-managed RUSLE2 climates, CLIGEN, and WINDGEN. For an individual field, the centroid

latitude and longitude are used to establish the climate input data. The RUSLE2 climate data are pulled in for the county where the centroid is located. The CLIGEN and WINDGEN databases use an interpolation algorithm to calculate climate data based on triangulation of nearby weather stations. Land management data are provided by an NRCS-managed database, which is housed in the integrated model as an XML data structure. Management data are a field-scale characteristic.

The variable-rate removal operations were modeled as a direct bale unit where a large square baler is pulled and powered by the combine harvester and receives residue material directly from the separation units within the harvester. This

was modeled assuming machine adjustments through the header and the separation units. For removal rates from 25 to 50%, the header height was assumed to be standard for current commercial harvest operations, and a control system within the harvester separation unit was assumed to adjust the quantity of material entering the baler. For removal rates from 50 to 80%, the header height was assumed to be adjusted lower, moving more of the plant residue through the harvester and then to the baler. The standard corn header was exchanged for a row crop header, and machine performance impacts of this configuration were not considered in this study. Based on this, the direct bale residue harvest operation was modeled from 25 to 80% removal at 5% increments. Including the potential for no removal, this creates 13 potential removal rates.

The integrated model was run at each yield data point within a field for the complete set of crop rotation/residue removal combinations. Sustainable removal rates from 0 to 25% are modeled and binned at 0% removal; 25 to 29.9% are binned at 25% removal with that schema, continuing to 79.9% removal. Sustainable removals from 80 to 100% are binned at 80% removal. Residue harvest at each yield point was evaluated for sustainability, thus requiring total wind- and water-induced soil erosion to be less than or equal to the tolerable soil loss level identified by NRCS for the particular soil and the SCI to be greater than or equal to zero. The highest removal rate satisfying these criteria was established as the removal rate for each yield point with the assumption that the harvesting equipment could make these adjustments on the fly. Executing this analysis resulted in approximately 15,600 model executions per hectare (400 spatial elements, 13 residue removal scenarios, and three model executions per spatial element).

Results and Discussion

The subfield scale model scenarios described previously were run for each of the three fields, and the results are shown in Fig. 2, 3, and 4. Field 1 has diverse soil characteristics, with soil organic
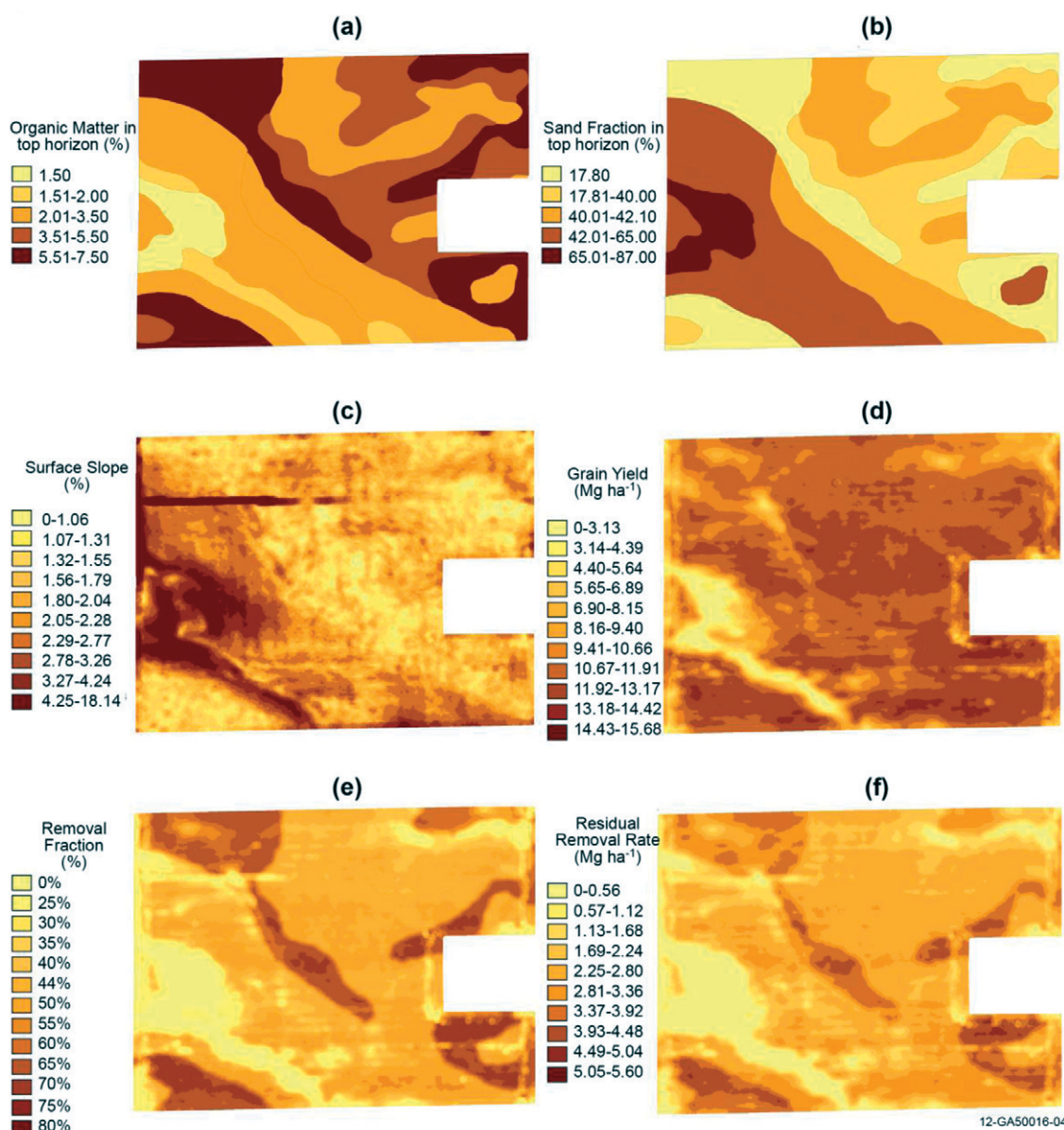

Fig. 2. Field 1 soil organic matter and sand fraction in the top soil horizon, surface slope, grain yield, and variable-rate removal results.
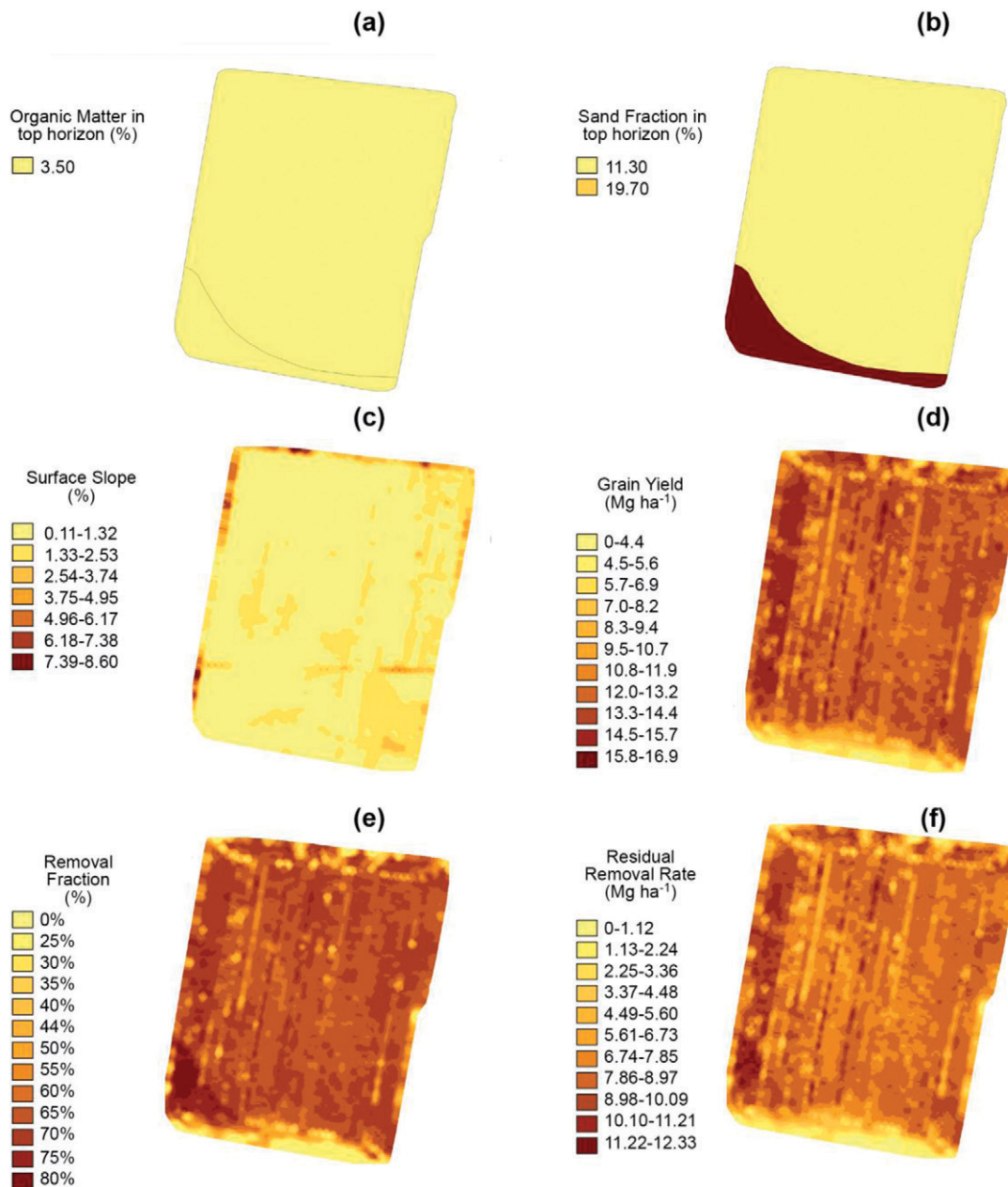
Fig. 3. Field 2 soil organic matter and sand fraction in the top soil horizon, surface slope, grain yield, and variable-rate removal results.

matter ranging from 1.5 to 7.5% and sand fractions ranging from 17.8 to 87.0% in the top horizon of the soil (Fig. 2). A higher sand fraction can indicate a tendency for greater wind erosion losses. Areas of low organic matter and high sand fraction correlate with the higher surface slopes (Fig. 2c). The areas of higher surface slopes in Field 1 represent hilltops. These field characteristics have a negative impact on grain yield (Fig. 2d). Muth et al. (2012) determined that only 21% of Field 1 would be managed sustainably with rake and bale residue removal due to the significant diversity in soil and surface slope characteristics and because the NRCS guidelines find that rake and bale residue removal is not sustainable for this field. Figure 2e shows the sustainable residue removal fraction across Field 1 for the land management assumptions as listed in Table 2. The sustainable residue removal ranges from 0 to over 5 Mg ha^{-1} (Fig. 2f). A visual comparison finds that areas with low grain yield do not sustainably support

residue removal. Specifically, for grain yields below approximately 5 Mg ha^{-1}, the minimum removal rate of 25% modeled for the conceptual variable-rate removal configuration is too high for sustainable removal. A visual comparison of Fig. 2a and 2e also shows that the sustainable removal fraction increases in areas of the field where soil organic matter is higher. The SSURGO soil map units shown in Fig. 2a are soil survey data, and the explicit transitions between different organic matter levels seen in Fig. 2a will be continuous in the field. In the same way, if higher resolution soils data were to become available, the explicit transitions to higher residue removal rates for the variable-rate harvester in Fig. 2e would have transitions that are more continuous. The accuracy of the subfield integrated model and consequently the conceptual variable-rate removal configuration are dependent on the quality and resolution of the soils data available.
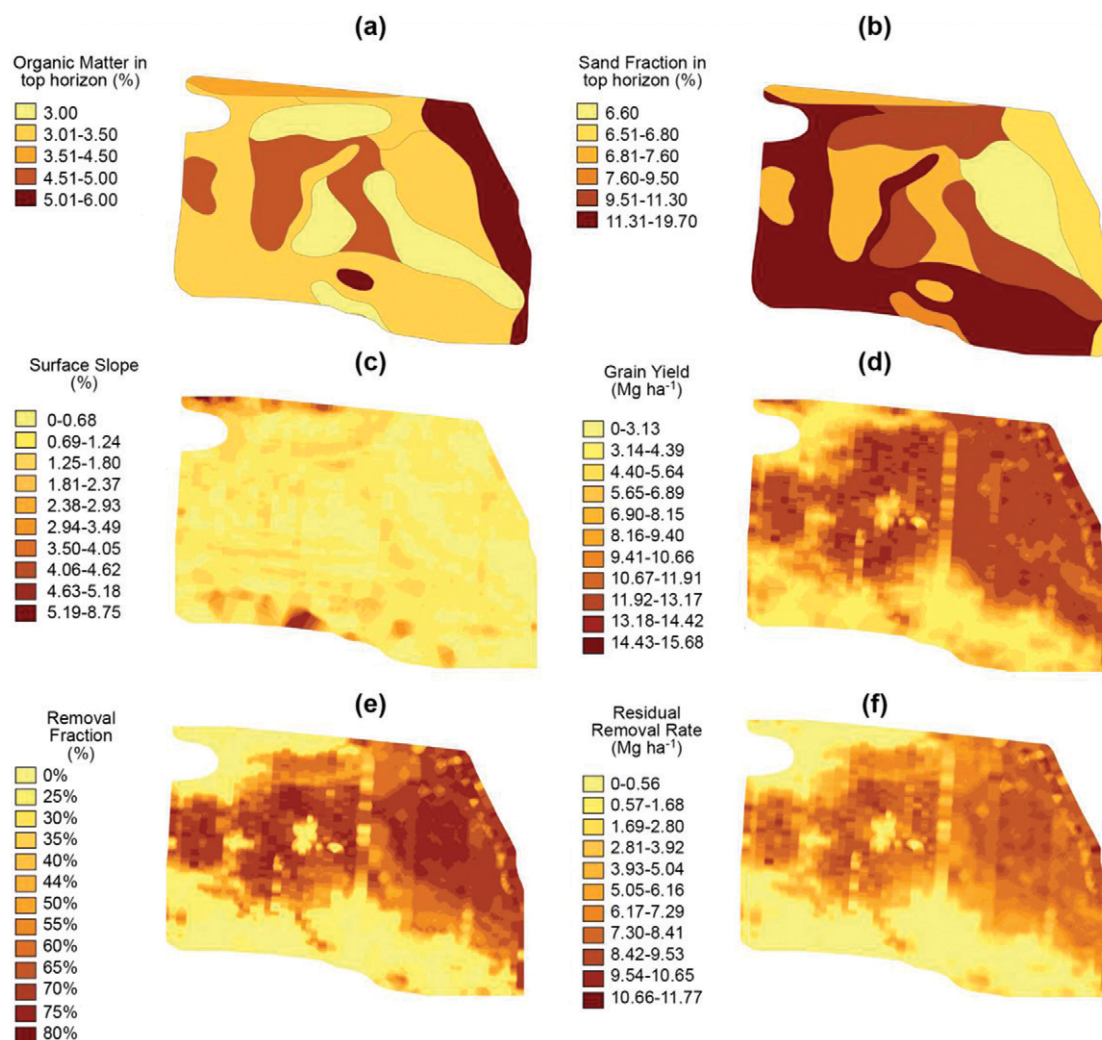
Fig. 4. Field 3 soil organic matter and sand fraction in the top soil horizon, surface slope, grain yield, and variable-rate removal results.

Field 2 is managed with a continuous corn rotation and reduced tillage practices (Table 2). This field has minimal soil and surface slope diversity (Fig. 3a and 3b). Grain yields are generally high in this field, and the rake and bale residue removal operations were found to be sustainable for 83% of Field 2 using the subfield scale integrated model (Muth et al., 2012). The fractional residue removal map using the conceptual variable-rate residue harvester shows that the majority of the field sustainably supports removal rates of 60% or greater (Fig. 3e). Because soil and surface slope conditions in Field 2 are generally uniform, the residue removal rates look similar to the grain yield map (Fig. 3d). Small pockets of lower grain yields along the edges of and in locations within Field 2 lead to little or no residue sustainably available with the variable-rate harvester in these areas. The majority of Field 2 can sustainably provide residue removal of approximately 5 Mg ha^{-1} or greater (Fig. 3f).

Field 3 is modeled in a continuous corn rotation using conventional tillage practices. Field 3 has moderate diversity in soil characteristics compared with Fields 1 and 2 (Fig. 4a and 4b). Surface slope in Field 3 is generally uniform and low at less than 1.5% for most of the field (Fig. 4c). Grain yield is highly variable in Field 3 (Fig. 4d). Significant portions of the field had grain yields less than 4.5 Mg ha^{-1}, and large areas of Field 3 also had relatively high grain

yields above 13 Mg ha^{-1}. The sustainable residue removal fraction map using the variable-rate residue harvester shows that areas of high grain yield correlate with high removal fractions above 65% (Fig. 4e). The removal rate map in Fig. 4f directly relates to the grain yield variability in Fig. 4d. A significant area in Field 3 cannot have any residue removed sustainably, but large portions of the field can sustainably provide over 8.5 Mg ha^{-1} of residue.

Figures 5a through 5c show the mass fraction of residue removed sustainably and the area fraction of residue harvested by bin for each of the three fields. Nearly 13% of the area in Field 1 requires a 0% removal rate to be sustainably managed (Fig. 5a). The 45% removal rate covers the most area and provides the most residue mass for Field 1 of the range of removal rates. Higher removal rates provide more residue per unit area, and Fig. 5a shows that, although the 65% removal rate is only used for about 12% of the field, it provides nearly 20% of the total residue mass sustainably available in Field 1. The results in Fig. 5a show that to collect 90% of the sustainably removable residue, the variable removal rate harvester would need to be capable of on-the-fly rate adjustments from 40 to 65%. The requirements are different when considering harvester performance for sustainably managing a land area. In this case, the variable-rate harvester would need to be able to make on-the-fly adjustments
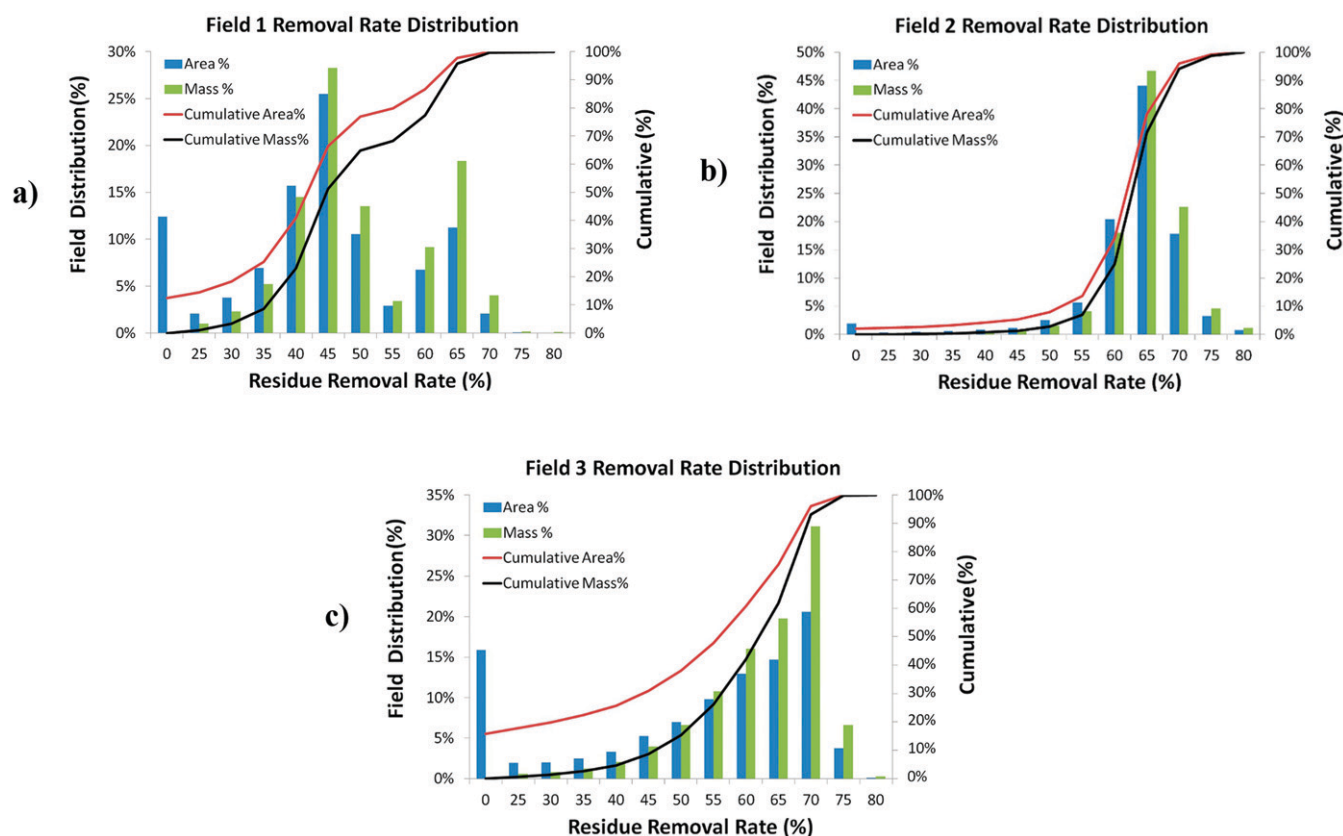
Fig. 5. Removal fraction distribution for variable-rate harvest scenarios in each of the three fields.

down to 0% removal to achieve sustainable removal for 100% of the area in Field 1. Accounting for both maximizing residue mass collected and sustainably managing a land area requires a robust and dynamic variable-rate residue harvester in Field 1.

Figure 5b shows that lower diversity in the subfield characteristics found in Field 2 create different variable-rate residue harvester performance requirements than the more diverse Field 1. Looking at Fig. 5b, the 65% removal rate is used for over 40% of Field 2. When 5% removal rate adjustments to 60 and 70% are included, nearly 80% of Field 2 is represented. Figure 5b shows that if the harvester has the ability to adjust between 60 and 70% removal rates, over 90% of the sustainably removable residue mass would be collected in Field 2. These results show that the uniform subfield characteristics in Field 2 result in much less intense variable-rate residue harvester performance requirements to achieve sustainable practices and maximize residue removed than found for Field 1.

Over 15% of the area in Field 3 requires no residue harvest, and over 35% of the area in the field requires removal rates at or below 50% (Fig. 5c). In contrast, the majority of the sustainably available residue mass will be collected at removal rates at 60% or above. Field 3 presents a scenario where on-the-fly removal rate adjustments within the variable-rate harvester need to cover the full range of the modeled assumptions to sustainably manage the land and maximize sustainably removed residue mass.

One question that arises is whether the full range of 25 to 80% is needed or if a smaller range of residue removal would be nearly as effective. In Field 1, a variable-rate harvester with the capability to adjust between 40 and 65% residue removals would collect 91% of the sustainably removable residue mass. In Field 2,

the variable-rate harvester would need to adjust between 60 and 70% removal rates to collect 92% of the sustainably removable material. For Field 3 to achieve 90% removal of the sustainably available residue would require removal rate adjustments from 50 to 70%. Therefore, if the variable-rate harvester was able to make on-the-fly adjustments from 40 to 70% removal rates, more than 90% of the sustainably available residue would be removed from each of these fields.

For each of the three fields, Table 4 compares the variable-rate residue removal scenario in this study to the current NRCS guidelines for sustainable rake and bale removal of the entire field and the selective subfield rake and bale single-rate residue removal scenario discussed in Muth et al. (2012). The selective subfield rake and bale removal scenario assumes, for purposes of the analysis, that rake and bale removal could effectively be turned off in sections of the field where the operation was found to be unsustainable. The sustainable removal rates of agricultural residue for the conceptual variable-rate removal equipment were 2.35, 7.69, and 5.62 Mg ha^{-1} for Fields 1, 2, and 3, respectively. In contrast, the sustainable removal rates using rake and bale removal and NRCS guidelines for the entire field were 0.0, 6.40, and 5.06 for Fields 1, 2, and 3, respectively. In addition, the variable-rate residue removal sustainably managed 100% of the land area in all three fields. In contrast, Field 1 could not be sustainably managed using rake and removal, and 83% of the land area of Field 2 and 62% of the land area of Field 3 were managed sustainably using rake and bale removal for the entire field. The selective rake and bale residue removal harvest of 21% of Field 1 provided 0.62 Mg ha^{-1}, and, as a consequence, it is likely that this field could not be harvested sustainably and

Table 4. Evaluation of residue removal using the subfield model. This table contrasts rake and bale removal without sustainability considerations, rake and bale removal as directed by Natural Resources Conservation Service conservation management planning, rake and bale removal only in areas where the subfield analysis identifies the operations as sustainable, and the conceptual variable-rate residue harvester.

Field	Total residue available with rake and bale removal if sustainability is not considered	Sustainable residue available with rake and bale removal based on NRCS† guidelines	Average annual sustainable removal rate with rake and bale removal based on NRCS guidelines	Sustainable residue available with selective rake and bale removal‡	Average annual sustainable removal rate with selective rake and bale removal‡	Sustainable residue removal with conceptual variable-rate assumptions	Average annual sustainable removal rate with conceptual variable-rate removal assumptions
	———— Mg ————		Mg ha⁻¹	Mg	Mg ha⁻¹	Mg	Mg ha⁻¹
1	152	0	0.00	35	0.62	133	2.35
2	119	119	6.40	106	5.70	144	7.69
3	387	387	5.06	279	3.65	430	5.62

† Natural Resources Conservation Service.

‡ Data from Muth et al. (2012).

economically. Selective rake and bale harvest of Fields 2 and 3 managed the entire land sustainably but only harvested 83 and 62% of the land area, respectively, and provided lower residue yields (5.70 and 3.65 Mg ha⁻¹, respectively) relative to current NRCS practice.

The investigation described in this paper assessed the potential of variable-rate residue removal technology for increasing sustainably removable residue and characterizes the performance of the conceptual variable-rate harvester required to maximize sustainable removal of residue. This analysis was performed for three representative Iowa fields. Subfield scale variability in soil characteristics, topography, and yield significantly affect sustainably available residue removal rates in all three fields. In each of the fields, variability in one or more of these items led to a wide range in sustainable residue removal in different areas of the field. For Field 1, soil properties had a large impact on the residue availability, whereas in Fields 2 and 3 the sustainable residue removal rates correlated to grain yield. In each field there were areas where no residue was sustainably available and areas where large portions of the available residue could be removed sustainably.

It was found that variable-rate residue harvest technologies support the challenging goals of optimizing residue removal for sustainable land management and bioenergy production. Compared with NRCS guidelines that suggest that no residue could be sustainably removed in Field 1, the conceptual variable-rate residue harvester modeled here would sustainably manage 100% of the land area while providing an average of 2.35 Mg ha⁻¹ of residue for energy use. In Fields 2 and 3, variable-rate harvesting provided 1.29 and 0.56 Mg ha⁻¹ more residue, respectively, than NRCS guidelines using rake and bale removal while sustainably managing 100% of the land area. The results of this analysis suggest that variable-rate removal of agricultural residue could sustainably provide more agricultural residue for energy production while improving sustainable management of land resources. Several challenges must be confronted for practical implementation of the conceptual variable-rate removal system investigated here. First, agricultural residues have a limited market and are less valuable than grain. It is unlikely that new equipment will be purchased specifically to support residue removal. A potential solution to this problem is the development of low-cost enhancements for existing combine harvesters that support the removal rate adjustments of 40 to 65%, which this study found to be sufficient for removing 90% of the sustainable residue. Another challenge for commercial implementation is real-time calculation of

sustainable removal rates. The integrated model presented here provides a foundation for developing this capability. Every input variable for the model other than grain yield is available before harvest. Several computational techniques are available that can reduce the detailed model developed here to a computationally tractable, real-time algorithm for producing the sustainable residue removal rate.

Acknowledgments

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